MPRA
Munich Personal RePEc Archive

Revising empirical linkages between direction of Canadian stock price index movement and Oil supply and demand shocks: Artificial neural network and support vector machines approaches

Abderrazak Dhaoui and Mohamed Audi and Raja Ouled Ahmed Ben Ali

University of Sousse, Tunisia, Faculty of Economic Sciences and Management, University of Sousse, Tunisia, Faculty of Economic Sciences and Management, University of Sousse, Tunisia, National Engineering School of Sousse

7. August 2015

Online at http://mpra.ub.uni-muenchen.de/66029/
MPRA Paper No. 66029, posted 13. August 2015 09:34 UTC

Revising empirical linkages between direction of Canadian stock price index movement and Oil supply and demand shocks: Artificial neural network and support vector machines approaches[1]

Abderrazak DHAOUI [a*], Mohamed AYDI [b], Raja OULED AHMED [c]

[a] *University of Sousse, Tunisia, Faculty of Economic Sciences and Management, Department of Econometrics and Management.*

[b] *University of Sousse, Tunisia, Faculty of Economic Sciences and Management.*

[c] *University of Sousse, Tunisia, National Engineering School of Sousse, Department of Mechanic.*

Abstract

Over the years, the oil price has shown an impressive fluctuation and isn't without signification impact on the evolution of stock market returns. Because of the complexity of stock market data, developing an efficient model for predicting linkages between macroeconomic data and stock price movement is very difficult. This study attempted to develop two robust and efficient models and compared their performance in predicting the direction of movement in the Canadian stock market. The proposed models are based on two classification techniques, artificial neural networks and Support Vector Machines. Considering together world oil production and world oil prices in order to supervise for oil supply and oil demand shocks, strong evidence of sensitivity of stock price movement direction to the oil price shocks specifications is found. Experimental results showed that average performance of artificial neural networks model is around 96.75% that is significantly better than that of the Support Vector Machines reaching 95.67%.

Keywords: Oil price; Stock price movement; Oil supply shocks; Oil demand shocks; Artificial neural networks model, Support Vector Machines.

JEL Classification: G12; Q43.

Introduction

Oil price has experienced a series of shocks for more than fifteen years. These shocks are not without impact on the industrial sector and therefore on economic growth and financial stock market development. More specifically stock market prices are highly sensitive to the oil price shocks. This sensitivity of stock prices to oil price shocks have been the subject of many works such as those of Jones and Kaul (1996), Sadorsky (1999), Huang et al. (1996), El-Sharif et al. (2005), Naifar and Al Dohaiman (2013), Chang and Yu (2013), Dhaoui and Saidi (2015), Mohanty, et al. (2011), and Nguyen and Bhatti (2012).

---

[1]The views expressed herein are those of the authors and do not necessarily reflect the views of their institutions.

[*] Corresponding author. Tel.: +216 73 301 808; *Fax*: +216 73 301 888; *E-mail address*: abderrazak.dhaoui@yahoo.fr

While Huang et al. (1996) results show non-significant impact of oil price shocks on stock returns shocks for some specific markets such as that of the S&P 500 stock market, several studies such as those of Nandha and Faff (2008), Papapetrou (2001), Sadorsky (1999), Issac and Ratti (2009), and Shimon and Raphael (2006) show negative connections between stock returns and oil price increases.

To supervise the stock returns behavior following the changes in oil price, different studies added other variables allowing to investigate the direct and indirect connections between oil price shocks and stock returns. Among others oil production is introduced as an explanatory variable by Kilian (2009), Kilian and Park (2009) and Güntner (2013). Bernanke et al. (1997) and Lee et al. (2012) introduced the short-term interest rate. Sadorsky (1999), Park and Ratti (2008), Cunado and Perez de Gracia (2003, 2005, 2014), and Dhaoui and Saidi (2015) developed models that associate the stock returns to the different variables including oil price, oil production, short-term interest rate and industrial production.

Many of statically methods used to examine the empirical linkage between oil price fluctuation and stock market returns are based on traditional classification techniques such as logistic regression or discriminant analysis. However, in recent times non-linear approaches and/or learning machines based approaches such as Kernel SVM and ANN have been applied to stock market movement prediction in several studies such as that of Kara et al. (2011) among others.

The contribution of this paper in economic and financial literature is twofold: (i) it presents a framework that identifies the most relevant attributes based on separate oil price shocks (OSS and OSD), and (ii) proposes alternative accurate and robust model to accurately predict the direction of movement of stock market series often characterized by their complex dimensionality, their non linearity and the presence of tremendous noise and a non-stationary characteristics. We propose two technical models namely ANN and SVM since they are shown as "*are accurate, robust to noise, and computationally efficient*" (Evgeniou et al., 2005) and that their predictive ability outperform competing classical models in which the multinomial logit models (Cui and Curry, 2005) and econometric approaches (Kara et al., 2011).

This study provides empirical linkages between oil price shocks and stock prices movement using monthly data for the Canadian stock market over the period starting January 1995 to December 2014. Two classification techniques based models are used to predict the direction of movement as a response to the stock market returns to oil price shocks. The analysis included supply and demand shocks to take into consideration the asymmetric response of stock prices to these two types of shocks. The main results we found show that artificial neural networks (96.75% in average) outperform the Support Vector machines (95.67% in average) in predicting the direction of movement of Canadian stock price movement as a response to oil supply and demand shocks.

The remainders of this paper proceed as follows. Section 2 reviews the literature on the sensitivity of stock market returns to oil price chocks and describes ANN and SVM. Section 3 focuses on the empirical analysis. In this section we present the variable definitions and the modeling approach. In particular, we describe the application of the proposed approaches. The discussion of empirical findings is the subject of the section 4. And finally, section 5 concludes.

2. Literature review

Oil prices have experienced a series of shocks over the decades (see Figure 1). Oil prices have been fluctuating significantly since the famous oil price shocks of the 1970s and the way until today. These enormous movements play a key role in creating a great uncertainty in the energy sector. During the period 2007 and 2008, the oil price has increased from 60$ to pass the psychological barrier of 100$ and reached the price of 147$ by barrel in July 2008. In August of the same year, prices started to drop to reach only 115$. Four months later, the prices dropped back considerably and got traded at 45$ at the end of December 2008. Another spectacular cycle started around March and April 2009 when oil was traded at about 40 dollars per barrel and ended up hitting the 70 dollars per barrel in August. More recently and in the first half of January 2014, the Brent oil crude was traded at more than 107 dollars per barrel. It is now traded at around 60$ after being around 40$ in December 2014. These important variations in oil prices do greatly affect consumers, producers and Markets. Product costs, trading strategies and incentives for new investments in technology or other sectors are seriously impacted by these changes in the price of this commodity. For more than fifty years now, these shocks have always had direct impact on the industrial sector and as a result on the economic growth and financial stock market development overall.

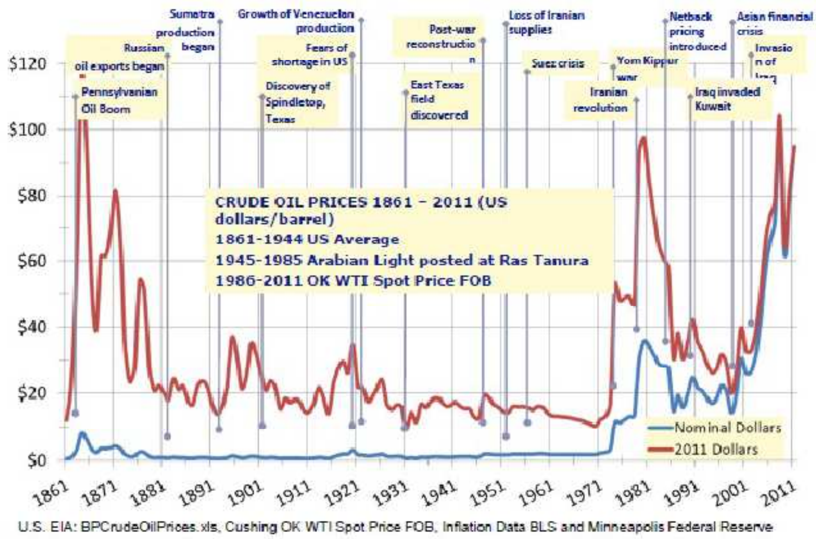

Figure 1: Crude oil price since 1861

As shown in Figure 2, various oil price cycles can be distinguish. Each cycle is associated to a regional or a global event that caused significant changes in the oil price (oil price shocks). The main events are (i) the Discovery of oil and using it as illuminants (1859-1899), (ii) the power and transportation (1900-1945), (iii) the postwar dislocations (1947-1948), (iv) the supply disruptions and the Korean conflict (1952-1953), (v) the Suez Crisis (1956-1957), (vi) the OPEC Embargo (1973-1974), (vii) the Iranian revolution (1978-1979), (viii) the Iran-Iraq War and the great price collapse (1980-1988), (ix) the First Persian Gulf War (1990-1991), (x) the East Asian Crisis (1997-1998), (xi) the Venezuelan unrest and the second Persian Gulf War (2002-2003), (xii) the new industrial age characterized by a growing demand and a stagnant supply (1997-2015).

Nowadays, it is accepted that oil price movement is not without critical influence on stock market prices (Arouri and Nguyen, 2010; Elyasiani et al., 2011; Nandha and Faff, 2008). Recent studies in this field recognize the significant speed and negative response of stock market on oil price shocks. However, although these important results other findings show non significant impacts. These mixed results are due to the asymmetric effect of oil price shocks. To supervise for these asymmetric effects, more recent works distinguish between oil supply and oil demand shocks to examine the sensitive response of (real) stock prices and returns to these shocks (Dhaoui and Saidi, 2015; Cunado and Gracia, 2014). Empirical findings show significant differences in sensitivity of stock market returns to oil demand and supply shocks in net oil importing and net oil exporting countries. Two channels conduct this sensitivity: indirect impact through an increase in short term interest rates, an increase in production costs,… and a direct impact in terms of response to information of an increase or a decrease in oil prices.

Recent researches in the field of finance are concentrated on the nature of linkages between the directions of movement of various financial instruments. Economists have, moreover, long been concerned with the problem of predicting the stock prices movement. The forecasts of the future movement of stock indexes or their returns are with great important for practitioner. It helps them to adapt their investment strategies. In this sense, Chen et al. (2003) recognized the effort they made both academic and practitioners to predict, firstly, the future evolution of the stock market components and to develop in the second round financial trading strategies to transform the forecasts into profits. Several statistical and econometric models are developed and different technical approaches are used such as the multinomial logit technical, the discriminant analysis, logit, probit... I recent years, numerous learning machine approaches are successfully applied to predict the direction of movement of stock price. In the present work we perform artificial neural networks (ANN) and a support vector machines (SVM) to better predict the direction of the movement of Canadian stock market returns. These techniques are the most artificial intelligence based systems used due their predictive ability that outperform competing models.

2.1. Artificial neural networks (ANN)

Many studies such as those of Avci (2007), Egeli, Ozturan, and Badur (2003), Karaatli, et al. (2005), Kimoto et al. (1990), Olson and Mossman (2003), White (1988), and Yoon and Swales (1991) have focused on studying the predictability of stock market. Various types of ANN were used to predict accurately the stock price returns and the direction of its movement. The results converge to show that ANN provides promising results in predicting stock price returns. Leung et al. (2000) compared different prediction models based on multivariate classification techniques such as discriminant analysis, logit, probit and probabilistic neural network to a large number of parametric and non-parametric models such as adaptive exponential smoothing, regression automotive vector with Kalman filter update, and the function of multivariate and multi-layer neural network transfer anticipation to examine their performance in forecasting the direction of the Index Return. The empirical findings demonstrate that the classification models outperform level estimation models in terms of both forecasting the direction of movement of the stock market and maximizing investment from trading returns. Chen et *al.* (2003) compared the probabilistic neural network (PNN) and the generalized methods of moments (GMM) with Kalman filter and random walk in predicting the direction of return on the Taiwan Stock Exchange Index. Empirical experimentations show that the ANN has a greater predictive power comparaed to the generalized methods of moments. Diler (2003) used various technical indicators including MA, momentum, RSI, stochastics K%, moving average convergence-divergence (MACD) to predict the direction of movment of the ISE 100 index. Using a neural networks model, the results show a prediction performance rate of 60.81%. Altay and Satman (2005) used neuronal networks models and ordinary least square to compare their forecast performance for both ISE-30 and ISE-All indexes. Using daily and monthly data empirical findings show that neural network models are able to predict the direction of the indexes more accurately despite their prediction performance failed to outperform the liner regression model. To demonstrate the accuracy of ANN to predict the movement of stock prices for firms listed in the Shanghai Stock Exchange Cao et al. (2005) compared the capital asset pricing model (CAPM) and Fama and french's 3 factors model to examine the predictive power of the univariate and multivariate neural network models. Empirical findings showed that neural networks outperform linear models.

Others authors such as Baba and Kozaki (1992), Chu et al. (2009), Hiemstra (1995), Kim and Chun (1998), Leigh, Purvis, and Ragusa (2002), Oh and Kim (2002), Pai and Lin (2005), Saad et al. (1998), Takahashi et al. (1998), Tan et al. (2007), and Yudong and Lenan (2009) tend to hybridize different artificial intelligence techniques to predict market returns. Tsaih et al. (1998) used a hybrid artificial intelligence to accurately predict the direction of daily price changes in S&P 500 stock index futures over a 6-year testing period from 1988 to 1993. The hybrid system integrates rule-based systems technique and neural networks technique. Empirical results demonstrated that reasoning neural networks (RN) outperform the other two ANN models (back propagation networks and perceptron). Empirical results also confirmed that the integrated futures trading system (IFTS) outperforms the passive buy-and-hold investment strategy.

2.2. Support vector machines (SVM)

In recent years, the Support Vector Machine, has been also largely and successfully used to forecast the movements of stock price index. Kim (2003) compared a SVM model to a back-propagation neural network (BPN) and a case-based reasoning (CBR) to examine if the SVM approach is capable to predict financial variables. He selected 12 technical attributes to predict the direction of the movement of daily stock price. The selected indicators includes stochastic K%, stochastic D%, stochastic slow D%, momentum, ROC, Williams' %R, A/D oscillator, disparity5, disparity10, OSCP, CCI and RSI. Experimental findings show that SVM outperform both BPN and CBR. The author concludes also that SVM constitutes a promizing alternative technique able to predict the stock market changes. Manish and Thenmozhi (2009) used different set of classification techniques to predict the daily movement of the Indian National Stock Exchange (S&P CNX NIFTY Market Index). The compared sets of techniques are (i) SVM and random forest, (ii) traditional discriminant and logit models, and (iii) ANN models. The input variables (attributes) they used to predict the direction of the daily stock index movement are the same used by Kim (2003). Experiment results show that SVM presented the best predictive power compared to the other of the calssification techniques such as random forest, neural network and other traditional models.)

Huang et al. (2005) compared the performance prediction of SVM different classification models such as the linear discriminant analysis, the quadratic discriminant analysis and the Elman backpropagation neural networks. Empirical findings show that SVM outperform the other model in forecasting the weekly movement direction of Nikkei 225 Index. In their study, Manish and Thenmozhi (2006) used ARIMA, ANN, SVM, and random forest regression models to investigate their usefulness in forecasting the S&P CNX NIFTY Index return. Empirical results of trading experiments showed that that the SVM are able to outperform the other models. To test the effectiveness of the architecture for stock price prediction, Hsu et al. (2009) developed tow stage architecture by integrating self-organizing map and compared its predictive performance with a single SVM. Using data sets for 7 stock market indices experiment results showed that the two stage architecture is more suitable for better predict the stock price movement.

3. Data and Methodology

3.1 Data description

To examine empirically the predictability of the stock price index movement following oil price shocks, we collect data for real stock prices, real industrial production, nominal interest rates and oil prices for the Canadian economy over the period from January 1995 to December 2014. The data used in this article are monthly. The starting date of the sample period is determined by the availability of monthly data serving to compute our variables. Monthly data are also used by Sadorsky (1999), Park and Ratti (2008), Driesprong et al. (2008), Lee et al. (2012), and Cunado and Perez de Gracia (2014), Dhaoui and Saidi (2015) among others. The variables used in our model are computed as follows.

Previous studies such as Cunado and Gracia (2014), Dhaoui and Saidi (2014), Sadorsky (1999), Park and Ratti (2008), Kilian (2009), Kilian and Park (2009) and Güntner (2013) used econometrics approaches to examine the linkages between oil price changes and stock returns. In this paper we present alternative techniques based on learning machines approach to predict the stock market return movement following the changes in some macroeconomic variables. Applying these based learning machines techniques the dependent variable will be introduced as output variable (label), while the explanatory variables will be introduced as input variables (attributes) in the ANN model (SVM, respectively).

Different data are used to compute the various inputs (attributes) and output (label) variables of our ANN (and SVM) models. The preliminary data includes real stock prices (*rsp*), real industrial production (*rip*), short-term interest rate (*r*), real national oil price (*op*), and real national oil production (*yoil*). The data for the oil price and the oil production are obtained from the Energy Information Administration (EIA) database and the International Financial Statistics (International Monetary Fund). The data for the real stock prices are obtained from the “OECD” and “EUROSTAT” databases. While, data for the others variables (*Real industrial production,* consumer price index, Short-term interest rates, exchange rate) are obtained from the “OECD” database and the Global Financial Data (GFD).

3.2. Variables definition

The detailed descriptions of the variables are discussed as following:

Real national oil prices (op). In this paper we use the real national price as a proxy for the oil price. The real national price is computed as the product of the nominal oil price and the exchange rate deflated by the consumer price index. The UK Brent nominal price is used as proxy for the nominal oil price. This proxy is commonly used by several authors such as Cunado and Perez de Gracia, (2003, 2005, 2014), Dhaoui and Saidi (2015) and Engemann et al., (2011) in order to investigate the type of interconnections between oil shocks and macroeconomic variables.

Real industrial production (rip). The real industrial production is computed as the nominal industrial production deflated by the consumer price index. Recent studies used this proxy are Sadorsky (1999), Park and Ratti (2008) and Cunado and Perez de Gracia (2014).

To supervise the behavior of stock markets return to the oil price shocks different aggregated variables are incorporated in the estimated model, that is, oil price, oil production, industrial production and short term interest rates. Further, the simultaneous use of both oil production and oil price allows to supervise for the asymmetric effects of oil supply and oil demand shocks. This variable is earlier used by Kilian (2009), Kilian and Park (2009) and Güntner (2013).

Besides, two variables are commonly used to supervise for the indirect impacts of oil price shocks on real stock returns namely, the short term interest rate and the industrial production.

In the major of cases, central banks react sensitively to higher oil prices through the short-term nominal interest rate. This reaction induces an indirect effect of oil price shocks on real economic activity and therefore on real stock market returns. The short-term interest rate constitutes, accordingly, a good proxy that allows monitoring the connections between oil price shocks on stock returns (Bernanke et al., 1997; Sadorsky, 1999; Park and Ratti, 2008; Lee et al., 2012; Cunado and Perez de Gracia, 2014). Oil price shocks exert also significant effect on the real economic activity since oil constitutes a substantial resource in the production process. Therefore, the real stock returns can be, indirectly, supervised using the industrial production variable.

Oil supply (resp., demand) shocks. Recent studies by Kilian (2009), and Peersman and Van Robays (2009), Cunado and Gracia (2014), Dhaoui and Saidi (2015) distinguish between oil supply and oil demand shocks. They consider that the effect of oil price changes can be supervised using separately the two types of shocks. In this study, we maintain the same specification proposed by Cunado and Gracia (2014) and Dhaoui and Saidi (2015). This specification of the oil supply and demand shocks can be as follows.

Let $\Delta op_t = op_t - op_{t-1}$ and $\Delta yoil_t = yoil_t - yoil_{t-1}$. These relations specify the Oil price variations and the world real oil production changes defined, respectively, as the first log difference of real oil prices and the first log difference of world real oil production.

The specifications of the oil supply shocks (Oss_t) and oil demand shocks (Ods_t) will be respectively as follows.

$$\begin{cases} Oss_t & = \Delta wop_t, \quad if \quad sign(\Delta op_t) \neq sign(\Delta yOil_t), \\ & = 0, \qquad otherwise\,. \end{cases} \tag{1}$$

$$\begin{cases} Ods_t & = \Delta wop_t, \quad if \quad sign(\Delta op_t) = sign(\Delta yOil_t), \\ & = 0, \qquad otherwise\,. \end{cases} \tag{2}$$

In other words, a demand shock occurs when oil price increases (decreases) together with world oil production increase (decrease). Oppositely, a supply shocks correspond to the case where the oil price increase (decrease) is followed by a world oil production decrease (increase).

The output variable represents the direction of real stock market return movement. Monthly changes in stock market return experienced to types of directions: increase and decrease. The status of changes is characterized as 0 or 1. If contemporaneous stock return is higher than that at time t-1, the direction in time t takes the value 1, otherwise, the direction is 0. The original data are nonlinear and are scaled into the range of [-1 1]. The linear scaling is motivated by the wishes to independently normalize each feature component to the specified range. The advantage of this scaling is twofold (Kim, 2003; Manish and Thenmozhi, 2005). Firstly, it ensures that larger value input attributes do not overhelm smaller value inputs. Secondly, it helps to reduce prediction errors. The real stock price (rsp) is computed as the difference between the stock price index and the inflation rate. Real stock returns, denoted Rt, is defined approximately as the first difference in the natural logarithms of the aggregate real stock market prices. It is computed based on the following specification: $R_t = \left(\ln(P_t) - \ln(P_{t-1})\right) \times 100$, where Pt is the real stock market index at the time t. The use of the real stock returns instead of the stock market returns is motivated by the wish to avoid the impact of the inflation rate. This proxy for the real stock return is already used by several authors sush as Park and Ratti (2008), Dhaoui and Saidi (2015) and Cunado and Gracia (2014).

4. Data preliminary analysis

4.1. Number of cases

The primary step in this study is to describe both the research data and the selection of predictor attributes.

This section describes the direction of stock market index movement in entire data sets and by period as well as the process of selection of the subsamples. The number of cases by period in the entire data is presented in Table 1. The total number of cases in the entire data set is 240 months. The number of cases with increasing direction is 128 representing about 53.33% while 112 cases have a decreasing direction corresponding to about 46.67%.

Table 1: The number of cases in the entire data set

	Period				
	1995-1999	2000-2004	2005-2009	2010-2014	Total
Increase	39	28	31	30	128
(%)	(65)	(47)	(52)	(50)	(53)
Decrease	21	32	29	30	112
(%)	(35)	(53)	(48)	(50)	(47)
Total	60	60	60	60	240

In a second step, we generalized different data sets. A first subset called “parameter setting data set” will be used in the preliminary experiments to determine the efficient parameter values for the two evaluated models. The parameter setting data set includes 20% of the entire data and is proportional to the number of direction cases observed in each period in the entire data set. The parameter setting data includes accordingly 26 increasing cases and 22 decreasing cases. Given such specific distribution of increasing and decreasing cases the parameter setting data set is capable to represent the entire data set. This latter was moreover divided into two equal subsample including 10% of the entire data set each one and representing data set for training and holdout. The number of cases for each period in the parameter setting data set is given in table 2.

Table 2: The number of cases in the parameter setting data set (20% of entire).

Period	Training (10%)			Hodout (10%)		
	Increase	Decrease	Total	Increase	Decrease	Total
1995-1999	4	2	6	4	2	6
2000-2004	3	3	6	3	3	6
2005-2009	3	3	6	3	3	6
2010-2014	3	3	6	3	3	6
Total	13	11	24	13	11	24

After specifying the efficient parameter values, the next step consists to perform the performance prediction on the entire data set considering the best parameter combination selected in the preliminary experiments. In this final prediction step the ANN and SVM model will be retrained using the entire data. This latter is specifically divided into training data set including 50% of entire data and holdout data set include the remaining 50% of entire data. Each subset must in addition be proportional to the number of increases and decreases of the entire data. Once the prediction performance is performed, the best accuracy of the two model will be compared. Table 3 summarized the number of cases in the prediction comparison data set.

Table 3: The number of cases in the comparison data sets.

Period	Training (50%)			Hodout (50%)		
	Increase	Decrease	Total	Increase	Decrease	Total
1995-1999	20	11	30	20	11	30
2000-2004	14	16	30	14	16	30
2005-2009	16	15	30	16	15	30
2010-2014	15	15	30	15	15	30
Total	64	56	120	64	56	120

4.2. Prediction models

Previous studies on oil price and stock returns applied classical technical analysis such as Arch and Garch model (Dhaoui and Khraief, 2014), Johansen cointegration model (Cunado and Gracia, 2014; Dhaoui and Saidi, 2015; Park and Ratti (2008),…). Other studies applied different classification model to predict the direction of stock prices movement using different attributes. The most used model are the Ordinary Least Square (OLS), the discriminant analysis, the logit and probit models, the and probabilistic neural network, the GMM-Kalman filter, the random walk prediction models, the capital asset pricing model (CAPM) and the Fama and French’s 3-factor model. Recent empirical studies converge to demonstrate the superiority of the artificial intelligence and machine learning based approaches in predicting the stock prices movement direction. Among all, ANN and SVM have commonly considered as the most able to outperform the competing models. They exhibit important insights and have gained reputation in terms of accuracy, robustness and computational efficiency in predicting the movement of economic and financial variables.

In recent times, the use of more complex non-linear techniques, such as neural networks and SVM have gained a lot of attention from various researchers when predicting the movement of stock market returns (Baesens et al., 2003). The ANN is, in fact, well suited for developing accurate prediction performance The SVM technique offers, however, several advantages compared to ANN such as absence of local minimas and relatively simple architecture.

The popularity of ANN and SVM compared to competing classification approaches including among other the logistic regression, the decision trees,… is due to the strong non linear mapping behavior of stock market data. These artificial intelligence approaches are widely used in non linear time series prediction.

Many works in stock market domain provide evidence that learning machine techniques can show performance comparable to traditional statistical techniques, such as discriminant analysis, prohibit analysis and logistic regression or to outperform them (Irwin et al., 1995; Paliwal and Kumar (2009). For Masters (1995) the use of these sophisticated techniques is highly recommended since they have the capability to more accurately model stock market data that exhibits interactions and curvature.

In this study, a three-layered feedforward ANN model was structured to predict stock price index movement. This ANN model consists of an input layer, a hidden layer and an output layer, each of which is connected to the other. The first layer is the input layer. It employed five neurons representing five technical inputs. The output layer employed a single neuron representing two patterns (0 or 1) of stock price direction of movement. The last layer is the hidden layer. The number of neurons in this layer varies by plots of 10 neurons from 10 to 100. The selected number is determined empirically in the experimental step. The architecture of the three-layered feedforward ANN is illustrated in Fig. 1.

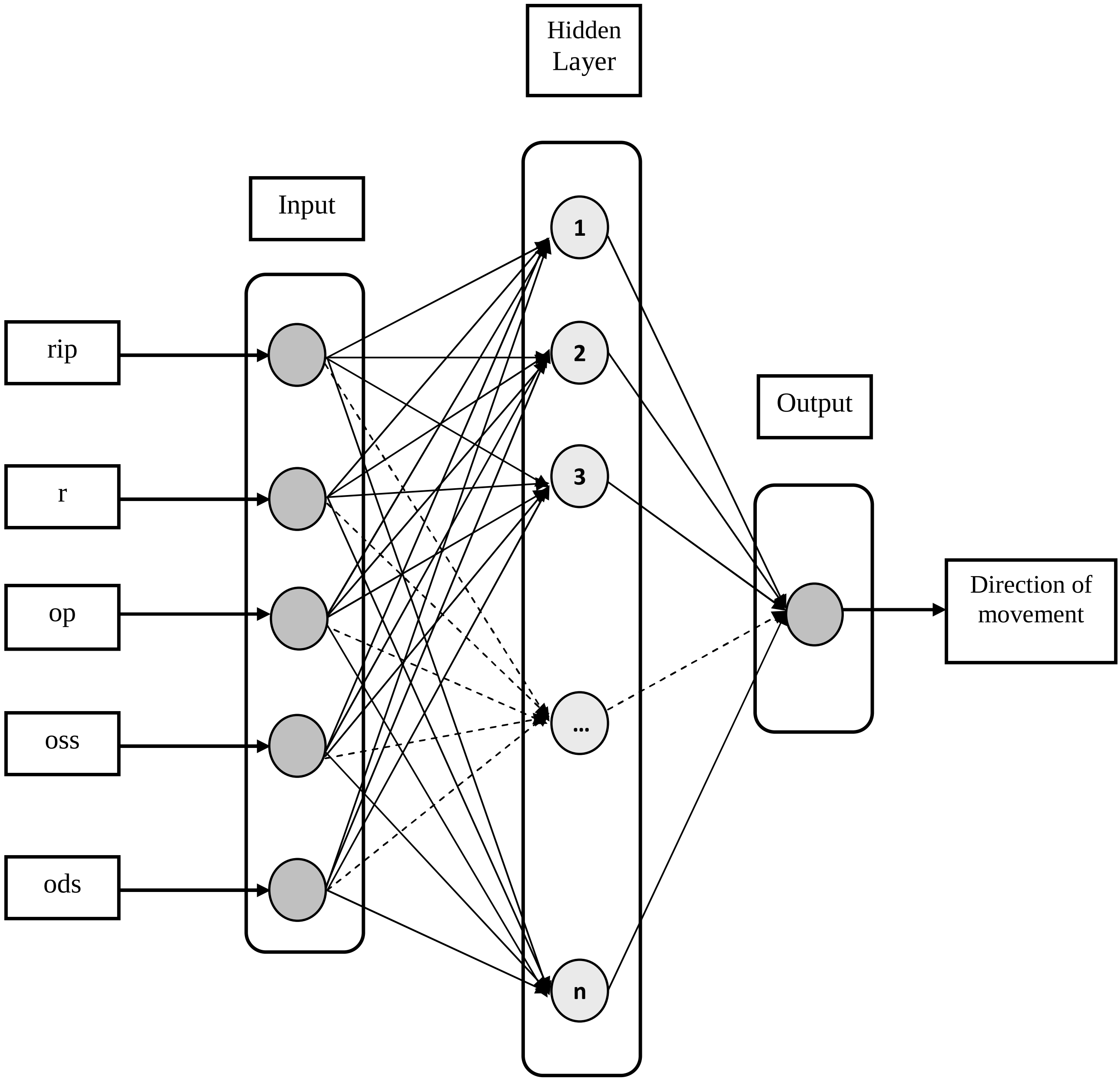

Figure 2 : The architecture of three layered feedforward artificial neural network.

Each neurons of the input layer is linked to the neurons of the hidden layer. At the same, all neurons of the hidden layer are linked to the neurons of the output layer. The linkages are expressed in connectivity coefficients (weights) which were adjusted, using a learning procedure, to ensure best classification of given input patterns for a given set of input-output pairs. The initial assignment of the values of these weights was random. In this study, we used the back-propagation learning algorithm to train the three layered feedforward ANN (Rumelhart et al., 1986). We evaluate the performance of the ANN model was evaluated by using the relative percentage of root mean square (RMS%). We used the gradient-descent method as the weight update algorithm to minimize RMS%. We select a tangent sigmoid transfer function on the hidden layer. We select, besides, a logistic sigmoid transfer function on the output layer which means that the outputs of our model will take the values 0 and 1.

Several ANN model parameters must be efficiently determined. That is, the number of neurons in the hidden layer (n), the value of learning rate (lr), the momentum constant (mc) and finally the number of iterations (ep). Based on previous empirical studies (e.g. Kara et al., 2011) we select ten level of n, ten level of ep and nine level of mc. We select a lr of 0.1 since a small level is commonly recommended in the literature. The ANN parameters and their levels are summarized in Table 1.

Table 1: Artificial neural network parameter levels tested in parameter setting (with lr=0.1)

Parameter										
Number of neurons (n)	10	20	30	40	50	60	70	80	90	100
Epochs (ep)	100	2000	3000	4000	5000	6000	7000	8000	9000	10000
Momentum constant (mc)	0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9	

A total of 900 parameter levels combinations are evaluated in parameter setting. All the combinations are applied to the training and holdout data sets. The prediction accuracy of the models is evaluated. All experiments are conducted using MATLAB. For each parameter combination we calculate both the training and the holdout performance. Then the average of training and holdout performances will be calculated. Three parameter combinations are selected corresponding to the three best average performances.

On the other hand, two models are performed for the support vector machines. That is radial and polynomial. For each model various parameter setting combinations are used in experimental tests. The parameter levels evaluated in parameter setting data for radial model include a total of 550 treatments, while, 110 treatments are performed for the polynomial model. Tables 2 and 3 summarized the various parameter combinations tested in parameter setting experiments for polynomial and radial SVM models, respectively. Similarly to the ANN model, the training performance of the polynomial model varied between 53% and 100% while the holdout performance varied between 46.8% and 97.1%. For the radial model, the training performance varied between 63.7% and 100%, while the holdout performance varied between 54.17% and 96.82%. We notice also that the best training and holdout performances are not obtained in the same parameter combinations. Consequently we calculated the average training and holdout performance and selected the parameter combinations corresponding to the best three average performances. The same approach is used in the three best parameter combinations in both polynomial and radial models.

Table 2: Support Vector Machine levels tested in parameter setting experiments (Polynomial Model)

Parameter for Polynomial modem											
Degree of kernel function (d)	1	2	3	4							
Regularization parameter (C)	1	10	20	30	40	50	60	70	80	90	100
Gamma in kernel function (c)	-	-	-	-	-	-	-	-	-	-	-

Table 3: Support Vector Machine levels tested in parameter setting experiments (Radial Model)

Parameter for Radial modem											
Degree of kernel function (d)	-	-	-	-	-	-	-	-		-	
Regularization parameter (C)	1	10	20	30	40	50	60	70	80	90	100
Gamma in kernel function (c)	0	0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9	1
	1,1	1,2	1,3	1,4	1,5	1,6	1,7	1,8	1,9	2	2,1
	2,2	2,3	2,4	2,5	2,6	2,7	2,8	2,9	3	3,1	3,2
	3,3	3,4	3,5	3,6	3,7	3,8	3,9	4	4,1	4,2	4,3
	4,4	4,5	4,6	4,7	4,8	4,9	5				

Given the advantages, the SVM has been largely used in time series for predicting the performance. Previous authors using such techniques are Kara et al. (2011), Cui and Curry (2005) among others. Similarly to the ANN, for many authors the SVM are accrute, robust to noise, and computationally efficient in a conjoint analysis context (Evgeniou et al., 2005). Their predictive ability outperform competing models such as multinomial logit models Cui and Curry (2005).

5. Empirical results and discussions

5.1. Experimental results

At the first stage we perform the experiments for parameter setting. For the ANN a total of 900 parameter combinations are tested. Table 4 gives the three best parameter combinations and the corresponding training and holdout performance accuracies for the ANN model.

Table 4: Best three parameter combinations of ANN model.

N°	lr	Ep	mc	N	Training	Holdout	Average
1	0.1	9000	0.9	10	100.00	100.00	100.00
2	0.1	9000	0.9	80	99.99	100.00	99.99
3	0.1	5000	0.8	100	99.99	100.00	99.99

The training performance of the ANN model for the 900 parameter combinations was varied between 51% and 100% while the holdout performance was varied between 50% and 100%. We should notice here that various parameter combinations allowed obtaining higher training and/or holdout performance. Moreover, the best training and holdout performance were not obtained at the same parameter combination. We calculate therefore the average performance of both training and holdout and select the three combinations corresponding to the best three average performances. Previous studies using this same selection process is Kara et al. (2011).

We follow the same procedure to select the best parameter combination for both radial and polynomial SVM models. We applied the SVM on the parameter setting subset. A total of 550 parameter combinations are tested for the Radial model and 110 combinations for the polynomial model. The training performance varied between 61% and 100% for the Radial model and between 62.5% and 100% for the polynomial model. At the same way, the holdout performance varied between 46.63% and 93.26% for the radial model and between 18.45% and 94.92% for the polynomial model. The best three combinations and corresponding performance for radial and polynomial SVM models are summarized in Table 5.

Table 5: Best parameter combinations of SVM models

N°	Kernel function	d	ɣ	C	Training	Validation	Average
1	Radial basis	-	0,1	10	100	91,73	95,86
2	Radial basis	-	0,2	1	100	95,38	97,69
3	Radial basis	-	2,2	20	100	96,24	98,12
4	Polynomial	1	-	50	97	96,46	96,73
5	Polynomial	2	-	50	100	96,86	98,43
6	Polynomial	10	-	10	100	96,05	98,02

As shown in Table 5, the training and holdout performances are in average the same in both radial and polynomial models. Taken separately, the holdout performances are about without significant difference from a parameter combination to another for the polynomial model. However, for radial model relative differences are shown event they may be supposed as without great significance.

5.2. Prediction performance results

The parameter combinations given in Table 4 for the ANN and Table 5 for the SVM (radial and polynomial models) are assumed to be the best ones in representing all cases in the entire data set. Based on these different combinations we perform the experiment comparisons for both ANN and SVM models. The data sets summarized in Table 3 were applied to the ANN and SVM models with their various best parameter combinations. The experiments were executed for each period separately. Tables 6 and 7 summarized the prediction performance of ANN and SVM, respectively.

Table 6: Prediction performance in percentage of artificial neural network model for best parameter combinations (lr = 0.1)

Period	(10; 9000; 0,9)		(80; 9000; 0,9)		(100; 5000; 0,8)	
	Training	Holdout	Training	Holdout	Training	Holdout
1995-1999	73,30	84,13	68,60	93,55	70,20	90,20
2000-2004	91,60	100,00	91,50	91,96	98,90	99,86
2005-2009	92,40	98,00	89,45	99,50	97,68	96,97
2010-2014	91,28	100,00	99,98	99,85	96,42	99,99
Average	87,14	95,53	87,38	96,21	90,80	96,75

Note: This table presented results training and holdout performance (%) of artificial neural network model for three best parameter combinations taking into account a learning rate of 0.1. The first line indicates the parameter combinations corresponding respectively to n, ep and mc.

As shown in Table 6, the average training and holdout performances of ANN model are about the same for the three different parameter combinations. However, although the approximately similar average performance, the third combination (100; 5000; 0,8) seems to be the best since it gives the relatively highest training performance accuracy (90.80%) and at same time the highest holdout performance one (96.75%).

To confirm that the parameter combination (n = 100; ep = 5000; mc = 0,8) is the best one, we accomplished an additional experiment to examine the effect of lr on the quality of prediction performance. Therefore, we fixed the other parameter values to their selected values and then we re-conducted all experiments by changing lr value. Testing eight new values (0,2; 0,3; … ;0,9) of lr, the average holdout performances are provided in Figure 3.

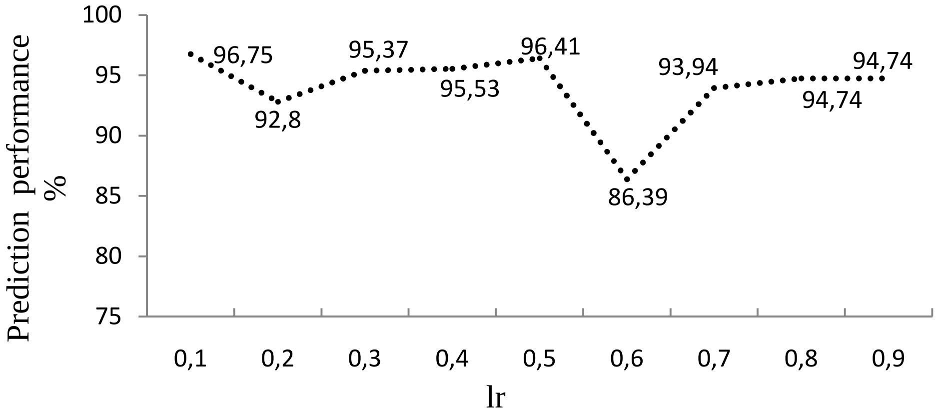

Figure 3: Performance (%) of ANN model for various lr values (n = 100, ep = 5000 ; mc = 0,8).

As shown in Figure 3, the best average holdout performance is reached at lr = 0,1. Thus, we confirm that the best parameter combination of ANN model is lr = 0,1; ep = 5000 ; mc = 0,8 and n = 1000 with an average holdout performance of 96.75% % . Accordingly, we adopt this parameter combination as a best to compare with that of SVM models.

Results in Table 6 show also that results differ from a period to another for a same selected parameter combination. Considering the best average performance parameter combination, we show that the highest holdout accuracy is obtained at the period 2010-2014 while the lowest is shown at the period 1995-1999. For the training performance, the highest accuracy is observed at the second performance (2000-2004) where the lowest corresponds to the first period (1995-1999).

Once the results for the ANN are presented and discussed, the results for the SVM models will be discussed in the following. Table 7 and 8 give the prediction performance in percentage respectively of polynomial and radial SVM model for the best parameter combinations.

Table 7: Prediction performance (%) of polynomial SVM for best parameter combinations

Parameter combination (d; c) (poly)						
Period	(1; 50)		(2; 50)		(10; 10)	
	Training	Houlout	Training	Houlout	Training	Houlout
1995-1999	100	90	100	89,25	100	86,33
2000-2004	100	90,53	100	92,03	100	91,37
2005-2009	100	95,38	100	93,34	100	95,66
2010-2014	100	91,88	100	87,92	100	88
Average	100	91.94	100	90.63	100	90.34

Table 8: Prediction performance (%) of polynomial SVM for best parameter combinations

Parameter combination (ɤ; c) (rad)						
Period	(1; 0,2)		(20; 2,2)		(10; 0,1)	
	Training	Houlout	Training	Houlout	Training	Houlout
1995-1999	100	96,66	100	94,27	100	92,74
2000-2004	100	90	100	91,39	100	95,09
2005-2009	100	99,28	100	95,66	100	99,4
2010-2014	100	93,67	100	90,86	100	95,47
Average	100	94,90	100	93.04	100	95.67

Results in Table 7 and 8 show that the results are about the same for the different parameter combinations taken separately for polynomial and radial SVM model. The average trading performance for the two models is the same and is at his highest level (100%). However, we show that the radial model presents greater holdout performance compared to the polynomial SVM model for different parameter combination. Moreover, the results shown on the two Tables, indicate that the performance accuracy differ from a period to another for the two models and for the different selected parameter combinations. The best average holdout performance parameter combination is d = 1 and c = 50 for the polynomial model and ɤ = 10 and c = 0.1 for the radial SVM model. Since the radial model provides the greater holdout performance accuracy, these later parameter combinations corresponding to the best SVM prediction performance model will be used in comparing results to those of ANN. The results of the T-Test of comparison of Mean for independent sample are summarized in Table 9.

Table 9: T-test for comparison of Means for independent sample

Model	N	Mean	Std. dev	Max	Min	t-student	P
ANN	4	96.75	4.58	99,99	90,20	2.030	0.089
Radial	4	95.67	2.76	99,4	92,74		

Results in Table 9 indicate that the difference between performances of ANN and Radial SVM models is significant at a 10% significance level. The ANN presents the best model predicting the direction of movements of the stock market returns.

Moreover, we can compare our results with those of previous studies using ANN and SVM model to predict the movement of the stock market returns. Table 10 summarized the average holdout performance observed in same previous studies.

Table 10: Comparison of results with similar studies

Diler (2003)	Altay and Statman (2005)	Kara et al (2011)			Our results		
ANN	ANN	ANN	SVM (polynomial)	SVM (Radial)	ANN	SVM (polynomial)	SVM (Radial)
60.81%	57.80%	75.74%	71.52%	62.82%	96.75%	91.94%	95.67%

Results in Table 10 show that our ANN model predicted the direction of movement of stock market returns more accurately compared to the studies of Diler (2003), Altay and Statman (2005) and Kara et al. (2011). Similarly, both polynomial and Radial SVM models present greater performance accuracy in our study compared to that of Kara et al. Although the approach seems the same used in the various studies the significant differences in performance accuracy are attributed to the specificities of the input and output variables used in each study. The effect of the time unit (weekly data monthly data, daily data) may also exert significant impact on the performance accuracy level. We notice, in addition, that we conducted ten trainings for every combination we tested, while, in their study, Kara et al. (2011) have tested one single times each combination. In our opinion, the number of training conducted improve the quality of forecasting since the selection of combinations with the best average performance will be more accurate once the number of trainings increase.

6. Policy implication and conclusion

Predicting the direction of movement of the stock market returns is an interesting and highly difficult task. As discussed in Leung et al. (2000) the accuracy and quality of stock price index movement predictions are fundamental for developing any effective market trading strategies. Using accurate predictions, investors can timely hedge against potential market risks while speculators would have profit-making opportunities when trading in the stock index. Successful prediction of the direction of movement of stock returns has usually an impact on the decision of a financial trader's to buy or sell an instrument. It usually attracts benefits for financial market investors. An accurate stock movement price predictions normally lead to development of the financial market as investor's confidence in achieving profits grow sustainably. This financial market stability and potential sustainable development has a direct positive impact on companies' investment capabilities. So, developing accurate stock movement forecasting models and tools is expected to have positive implications on the stock market. Besides its complex nature, the stock market is often influenced by several macro-economic factors such as political events, company's policies, economic conditions, investor's behaviors and expectations and institutional investor's choices etc.

Using data for Canadian stock market over the period 1995-2014 the empirical finding show that ANN and SVM models successfully predict the direction of movement of stock market returns at an accuracy average performance of 96.75% and 95.67% respectively. ANN and SVM are highly accurate and robust prediction models. Besides despite they constitute useful tools in financial time series prediction they suffer from some major limitations in learning the stock market patterns because the data used has tremendous noise, non-stationary characteristics, and complex dimensionality.

References

Altay, E., and Satman, M.H. (2005). Stock market forecasting : Artificial neural networks and linear regression comparaision in an emerging market. *Journal of Financial Management and Analysis*, vol. 18(2): 18-33.

Arouri, M., Dinh, T.H., & Nguyen, D.K. (2010). Time-varying predictability in crude oil markets: The case of GCC countries. *Energy Policy, 38*: 4371–4380.

Avci, E. (2007). Forecasting daily and sessional returns of the ISE-100 index with neural network models. *Journal of Dogus University*, vol. 8(2): 128-142.

Baba, N., & Kozaki, M. (1992). An intelligent forecasting system of stock price using neural networks. In Proceedings of the international joint conference on neural networks, Baltimore, MD, USA, pp. 371–377.

Baesens, B., van Gestel, T., Viaene, S., Stepanova, M., Suykens, J., & Vanthienen, J. (2003). Benchmarking state-of-the-art classification algorithms for credit scoring. *Journal of the Operational Research Society*, 54: 1082-1088.

Bernanke, B.S., Gertler, M., and Watson, M.W. (1997). Systematic monetary policy and the effects of oil shocks. *Brookings Papers on Economic. Activity*, 1: 91-157.

Cao, Q., Leggio, K.B., & Schniederjans, M.J.A. (2005). A comparaison between Fama and French's model and artificial neural networks in predicting the Chines stock market. *Computers & Operations Research*, 32: 2499-2512.

Chang, K.L., & Yu, S.T. (2013). Does crude oil price play an important role in explaining stock return behavior?. *Energy Economics*, 39: 159-168.

Chen, A.S., Leung, M.T., & Daouk , H. (2003). Application of neural networks to an emerging financial market : Forecasting and trading the Taiwan Stock Index. *Computer & Operations Research*, 30(6): 901-923.

Chu, H.H., Chen, T.L., Cheng, C.H., & Huang, C.C. (2009). Fuzzy dual-factor time-series for stock index forecasting. *Expert Systems with Applications*, 36(1): 165–171.

Cui, D., & Curry, D. (2005). Prediction in Marketing using the Support Vector Machine", *Marketing Science*, 24(4): 595-615.

Cunado, J., & Perez de Gracia, F. (2003). Do oil price shocks matter? Evidence for some European countries. *Energy Econmics*, 25: 137-154.

Cunado, J., & Perez de Gracia, F. (2005). Oil prices, economic activity and inflation: evidence for some Asian economies. *The Quarterly Review of Economics and Finance*, 45: 65-83.

Cunado, J., & Perez de Gracia, F. (2014). Oil price shocks and stock market returns: Evidence for some European countries. *Energy Econmics*, 42: 365-377.

Dhaoui, A. & Saidi, Y. (2015). Oil supply and demand shocks and stock price. Empirical evidence for some OECD countries. MPRA Paper No. 63556.

Dhaoui, A. & Khraief, N. (2014). Empirical Linkage between Oil Price and Stock Market Returns and Volatility, Evidence from International Developed Markets. *Economics Discussion Papers*, 2014-12, Kiel Institute for the World Economy. http://www.economics-ejournal.org/economics/discussionpapers/2014-12

Diler, A.I. (2003). Predicting direction of ISE national-100 index with back propagation trained neural network. *Journal of Istanbul Stock Exchange*, 7(25-26): 65-81.

Driesprong, G., Jacobsen, B., & Maat B. (2008). Striking Oil: Another Puzzle?. *Journal of Financial Economics*, 89(2): 307-327

Egeli, B., Ozturan, M., & Badur, B. (2003). Stock market prediction using artificial neural networks. In Kara, Y., et *al.* (2011).The third Hawai international conference on business, Honolulu, Hawai

El-Sharif, I., Brown, D., Burton, B., Nixon, B., & Russell, A. (2005). Evidence on the nature and extent of the relationship between oil prices and equity values in the UK. *Energy Economics*, 27: 819-830.

Elyasiani, E., Mansur, I., & Odusami, B. (2011). Oil price shocks and industry stock returns. *Energy Economics.* 33: 966–974.

Engemann, K.M., Kliesen, K.L., & Owyang, M.T. (2011). Do oil shocks drive business cycle? Some US and international evidence. *Macroeconomic Dynamics*, 15: 298-517.

Evgeniou, T., Boussios, C., & Zacharia, G. (2005). Generalized robust conjoint estimation. *Marketing Science*, 24(3): 415–429.

Güntner, J.H. (2013). How do international stock markets responds to oil demand and supply shocks?. *Macroeconomic Dynamics*, First View Article, pp. 1-26. DOI:http://dx.doi.org/10.1017/S1365100513000084.

Hiemstra, Y. (1995). Modeling structured nonlinear knowledge to predict stock market returns. In R.R. Trippi (Ed.), Chaos and nonlinear dynamics in the financial markets: Theory, evidence and applications (pp. 163–175). Chicago, IL: Irwin.

Hsu, S.H., Hsieh, J.J.P.A., Chih, T.C., & Hsu, K.C. (2009). A two stage architecture for stock price forecasting by integrating self-organizing map and support vector regression. *Expert Systrems with Applications*, 36(4): 7947-7951.

Huang, R., Masulis, R.W., & Stoll, H.R. (1996). Energy Shocks and Financial Markets. *Journal of Futures Markets*, 16(1): 1-27.

Huang, W., Nakamori, Y., & Wang, S.Y. (2005). Forecasting stock market movement direction with support vector machine. *Computer & Operatrion Research*, 32: 2513-2522.

Irwin, G.W., Warwick, K., & Hunt, K.J. (1995). Neural network applications in control. IEE control engineering series 53. London, UK: The Institution of Electrical Engineers.

Issac, M.J., & Ratti, R.A. (2009). Crude Oil and stock markets: Stability, instability, and bubbles. *Energy Economics*, 31: 559-568.

Jones, C.M., & Kaul, G. (1996). Oil and the Stock Market. *Journal of Finance*, 51(2): 463-491.
Kara, Y., Boyacioglu, M.A., & Baykan, Ö.K. (2011). Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istambul Stock Exchange. *Expert Systems with Apllications*, 38: 5311-5319.
Karaatli, M., Gungor, I., Demir, Y., & Kalayci, S. (2005). Estimating stock market movements with neural network approach. *Journal of Balikesir University*, 2(1): 22-48.
Kilian, L. (2009). Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. *American Economic Review*, 99(3): 1053-1069.
Kilian, L., & Park, C. (2009). The impact of oil price shocks on the US stock market. *International Economic Review*, 50(4): 1267-1287.
Kim, K. (2003). Financial time series forecasting using support vector machines. *Neurocomputing*, 55: 307-319.
Kim, S.H., & Chun, S.H. (1998). Graded forecasting using an array of bipolar predictions: Application of probabilistic neural networks to a stock market index. *International Journal of Forecasting*, 14: 323–337.
Kimoto, T., Asakawa, K., Yoda, M., & Takeoka, M. (1990). Stock market prediction system with modular neural networks. The international joint conference on neural network, San Diego, California.
Lee, B.J., Yang, C.H., & Huang, B.H. (2012). Oil price movements and stock market revisited: a case of sector stock price indexes in the G7 countries. *Energy Economics*, 34: 1284-1300.
Leigh, W., Purvis, R., & Ragusa, J.M. (2002). Forecasting the NYSE composite index with technical analysis, pattern recognizer, neural network, and genetic algorithm: A case study in romantic decision support. *Decision Support Systems*, 32(4): 361–377.
Leung, M.T., Daouk, H., & Chen, A.S. (2000). Forecasting stock indices : A comparision of classification and level estimation models. *International Journal of Forecasting*, 16: 173-190.
Manish, K., & Thenmozhi, M. (2006). Support vector machines approach to predict the S&P CNX NIFTY index return. In procedings of 10th Indian institute of capital markets conference, Mumbai , India.
Manish, K., & Thenmozhi, M. (2009). Forecasting stock index movement : A comparaison of support vector machines and random forest method. *IIMB Management Review*, 21(1): 41-51.
Manish., K. & Thenmozhi, M. (2005). Static and Dynamic Neural Network in Forecasting Exchange Rate Returns, Proceedings of conference on Research in Finance and Accounting, IIM Lucknow, India.
Masters, T. (1995). Advanced algorithms for neural networks: A C++ sourcebook, John Wiley & Sons, Inc.
Mohanty, S.K., Nandha, M., Turkistani, A.Q., & Alaitani, M.Y. (2011). Oil price movements and stock market returns: Evidence from Gulf Cooperation Council (GCC) countries. *Global Finance Journal*, 22: 42-55.
Naifar, N., & Al Dohaiman, M.S. (2013). Nonlinear analysis among crude oil prices, stock markets' return and macroeconomic variables. *International Review of Economics and Finance*, 27: 416-431.

Nandha, M., & Faff, R. (2008). Does oil move equity prices? A global view. *Energy Economics*, 30: 986-997.
Nguyen, C.C., & Bhatti, M.I. (2012). Copula model dependency between oil prices and stock markets: Evidence from China and Vietnam. *Journal of International Financial Markets, Institutions and Money*, 22(4):758-773.
Oh, K.J., & Kim, K.J. (2002). Analyzing stock market tick data using piecewise nonlinear model. *Expert Systems with Applications*, 22(3): 249–255.
Olson, D., & Mossman, C. (2003). Neural network forecasts of Canadian stock returns using accounting ratios. *International Journal of forecasting,* 19(3): 453-465.
Pai, P.F., & Lin, C.S. (2005). A hybrid ARIMA and support vector machines model in stock price forecasting. *Omega,* 33: 497-505.
Paliwal, M., & Kumar, U.A. (2009). Neural networks and statistical techniques: A review of applications. *Expert Systems with Applications*, 36(1): 2–17.
Papapetrou, E. (2001). Oil Price Shocks, Stock Market, Economic Activity and Employment in Greece. *Energy Economics,* 23: 511-532.
Park, J., & Ratti, R.A. (2008). Oil price shocks and stock markets in the US and 13 European countries. *Energy Economics,* 30: 2587-2608.
Peersman, G. & Van Robays, I. (2009). Oil and the Euro Area Economy. *Economic Policy,* 24(60): 603-651
Rumelhart, D.E., Hinton, G.E., & Williams, R.G., (1986). Learning representations by back-propagating ratios. *Nature*, 323: 533-536.
Saad, E.W., Prokhorov, D.C., & Wunsch, D.C. (1998). Comparative study of stock trend prediction using time delay, recurrent and probabilistic neural networks. *IEEE Transactions on Neural Networks*, 9: 1456-1470.
Sadorsky, P., (1999). Oil price shocks and stock market activity. *Energy Econmics*, 21: 449-469.
Shimon, A., & Raphael, S. (2006). Exploiting the Oil-GDP effect to support renewable development. *Energy Policy,* 34(17: 2805-2819.
Takahashi, T., Tamada, R., & Nagasaka, K. (1998). Multiple line-segments regression for stock prices and long-range forecasting system by neural networks, In Proceedings of the 37th SICE annual conference, Chiba, Japan (pp. 1127–1132).
Tan, T.Z., Quek, C., & See, Ng. G. (2007). Biological brain-inspired genetic complementary learning for stock market and bank failure prediction. *Computational Intelligence*, 23(2): 236–261.
Tsaih, R., Hsu, Y., & Lai, C.C. (1998). Forecasting S&P 500 stock index futures with a hybrid AI system. *Decision Support Systems*, 23: 161–174.
White, H., (1988). Economic prediction using neural networks : The case of IBM daily stock returns. The IEEE international conference on neural networks, San Diego, California.
Yoon, Y., & Lenan, W. (2009). Stock market prediction of S&P500 via combination of improved BCO approach and BP neural network. *Expert Systems with Applications*, 36(5): 8849-8854.
Yudong, Z., & Lenan, W. (2009). Stock market prediction of S&P 500 via combination of improved BCO approach and BP neural network. *Expert Systems with Applications*, 36(5): 8849–8854.